Uncovering inflation dynamics in Morocco: An ARIMA approach

NYONI, THABANI

University of Zimbabwe

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Nyoni, Thabani

Department of Economics

University of Zimbabwe

Harare, Zimbabwe

Email: nyonithabani35@gmail.com

ABSTRACT

This research uses annual time series data on inflation rates in Morocco from 1960 to 2017, to model and forecast inflation using ARIMA models. Diagnostic tests indicate that M is I(1). The study presents the ARIMA (0, 1, 1) model. The diagnostic tests further imply that the presented optimal ARIMA (0, 1, 1) model is stable and acceptable in forecasting inflation in Morocco. The results of the study apparently show that M will be hovering somewhere around 1.1% over the next decade. Policy makers and the business community in Morocco are expected to take advantage of the anticipated stable inflation rates over the next decade.

Key Words: Forecasting, Inflation, Morocco

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation is the sustained increase in the general level of prices and services over time (Blanchard, 2000). The negative effects of inflation are widely recognized (Fenira, 2014). Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) as it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado *et al*, 2013).

As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004). To prevent the aforementioned undesirable outcomes of price instability, central banks require proper understanding of the future path of inflation to anchor expectations and ensure policy credibility; the key aspects of an effective monetary policy transmission mechanism (King, 2005). Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialized economies is mandated to maintain price stability over the medium term (Buelens, 2012). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012).

The statute of Bank AlMaghrib (BAM), the central bank of Morocco, states that price stability is the prime objective of Morocco's monetary policy. In the meantime, BAM is also responsible for maintaining the MAD's (Moroccan Dirham) value – against a basket of to major currencies – within a very narrow band. Thereby, it relies on the exchange rate as a nominal anchor for its monetary policy. Furthermore, current restrictions on foreign assets purchasing by residents afford BAM som room for maneuver in setting its nominal interest rate so as to carry out domestic targets. This framework has permitted a moderate inflation and the insulation of Morocco's economy from nominal shocks over the past decade (IMF, 2014). To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability (Enke & Mehdiyev, 2014). In this study, we seek to model and forecast inflation in Israel using ARIMA models.

LITERATURE REVIEW

Nyoni (2018) studied inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni (2018) modeled inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; studied inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

MATERIALS & METHODS

Box – Jenkins ARIMA Models

One of the methods that are commonly used for forecasting time series data is the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976; Brocwell & Davis, 2002; Chatfield, 2004; Wei, 2006; Cryer & Chan, 2008). For the purpose of forecasting inflation rate in Morocco, ARIMA models were specified and estimated. If the sequence $\Delta^d M_t$ satisfies an ARMA (p, q) process; then the sequence of M_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d M_t = \sum_{i=1}^{p} \beta_i \Delta^d M_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \qquad [1]$$

which we can also re – write as:

$$\Delta^d M_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i M_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \qquad [2]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018).

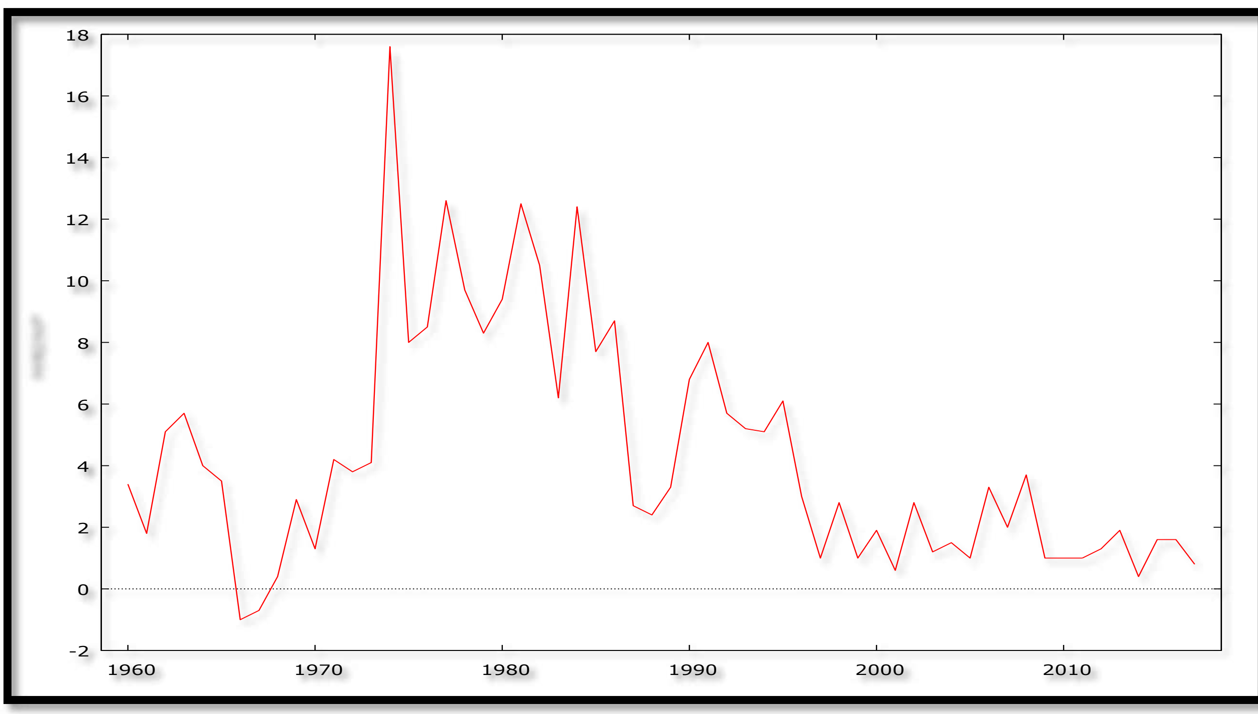
Data Collection

This study is based on a data set of annual rates of inflation in Morocco (MRINF or simply M) ranging over the period 1960 – 2017. All the data was taken from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Autocorrelation function for MRINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF		PACF		Q-stat. [p-value]
1	0.6613	***	0.6613	***	26.6954 [0.000]
2	0.5919	***	0.2748	**	48.4673 [0.000]
3	0.5571	***	0.1760		68.1047 [0.000]
4	0.4520	***	-0.0343		81.2690 [0.000]
5	0.3855	***	-0.0239		91.0284 [0.000]
6	0.2936	**	-0.0889		96.7963 [0.000]
7	0.2561	*	0.0177		101.2726 [0.000]
8	0.1438		-0.1301		102.7109 [0.000]
9	0.1201		0.0291		103.7350 [0.000]
10	0.1370		0.1061		105.0962 [0.000]
11	0.0332		-0.1054		105.1778 [0.000]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M	-2.15548	0.2245	-3.552666	@1%	Non-stationary
			-2.914517	@5%	Non-stationary
			-2.595033	@10%	Non-stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M	-3.601154	0.0386	-4.127338	@1%	Non-stationary
			-3.490662	@5%	Stationary
			-3.173943	@10%	Stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M	-1.378979	0.1542	-2.606911	@1%	Non-stationary
			-1.946764	@5%	Non-stationary
			-1.613062	@10%	Non-stationary

Figure 1 and tables 1 – 4 show that M is non-stationary in levels.

The Correlogram (at 1st Differences)

Autocorrelation function for d_MRINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 5

LAG	ACF		PACF		Q-stat. [p-value]
1	-0.4050	***	-0.4050	***	9.8481 [0.002]
2	-0.0469		-0.2523	*	9.9828 [0.007]
3	0.0993		-0.0340		10.5971 [0.014]
4	-0.0521		-0.0349		10.7693 [0.029]
5	0.0338		0.0230		10.8430 [0.055]
6	-0.0918		-0.0975		11.3984 [0.077]
7	0.1139		0.0489		12.2709 [0.092]
8	-0.1322		-0.1075		13.4708 [0.097]
9	-0.0401		-0.1462		13.5834 [0.138]
10	0.1692		0.0600		15.6310 [0.111]
11	-0.1385		-0.0423		17.0329 [0.107]

ADF Test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M	-7.834424	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M	-7.799466	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

Table 8: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M	-7.903513	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Tables 5 – 8 reveal that M is an I (1) variable since it is stationary in 1st differences.

Evaluation of ARIMA models (without a constant)

Table 9

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	284.8192	0.92586	-0.076313	1.8243	2.7879	71.623
ARIMA (1, 1, 0)	286.1169	0.99801	-0.05825	1.9817	2.871	75.281
ARIMA (0, 1, 1)	**282.8309**	0.9171	-0.077448	1.8213	2.7882	71.58
ARIMA (2, 1, 1)	286.4625	1.0067	-0.069314	1.8196	2.7792	72.129
ARIMA (1, 1, 2)	286.641	0.91938	-0.078823	1.8152	2.7838	72.783
ARIMA (2, 1, 2)	288.2758	0.99658	-0.071487	1.8195	2.7745	72.664
ARIMA (2, 1, 0)	284.5273	1.0365	-0.066368	1.8326	2.7808	72.866
ARIMA (0, 1, 2)	284.8161	0.92875	-0.075951	1.8251	2.7878	71.657

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018). The study will only consider the AIC as the criteria for choosing the best model for forecasting inflation in Morocco and therefore, the ARIMA (0, 1, 1) model is preferred.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (0, 1, 1) Model

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.419632	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.452084	0.0000	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

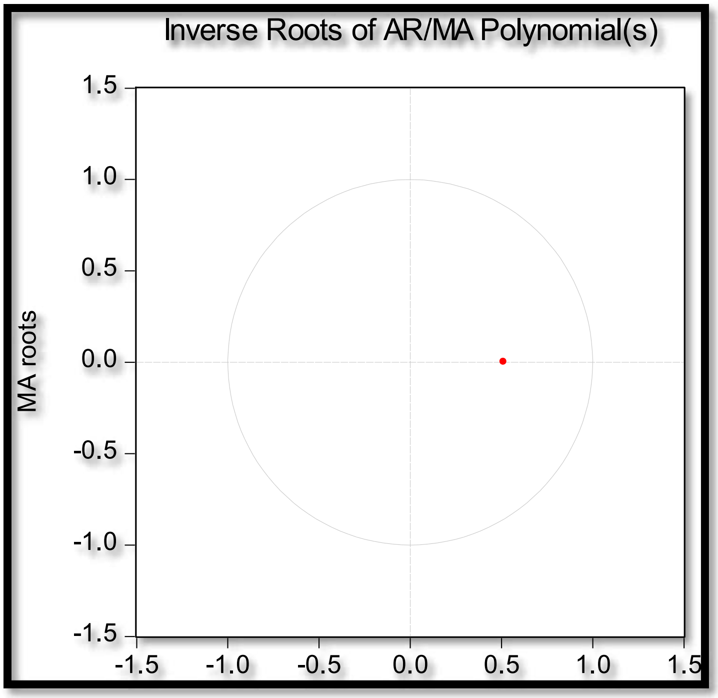
Table 12: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.485329	0.0000	-2.606911	@1%	Stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

Tables 10, 11 and 12 show that the residuals of the ARIMA (0, 1, 21 model are stationary and hence the ARIMA (0, 1, 1) model is suitable for forecasting inflation in Morocco.

Stability Test of the ARIMA (0, 1, 1) Model

Figure 2



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (0, 1, 1) model is stable and suitable for predicting inflation in Morocco over the period under study.

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	4.35
Median	3.3
Minimum	-1
Maximum	17.6
Standard deviation	3.8606
Skewness	1.1931
Excess kurtosis	1.1886

As shown above, the mean is positive, i.e. 4.35%. The minimum is -1% and the maximum is 17.6%. The skewness is 1.1931 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis was found to be 1.1886; implying that the inflation series is not normally distributed.

Results Presentation[1]

Table 14

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

ARIMA (0, 1, 1) Model:				
$\Delta M_{t-1} = -0.505026\mu_{t-1}$ ……………………………………………………………………………… [3]				
P: (0.0000)				
S. E: (0.1153)				
Variable	Coefficient	Standard Error	z	p-value
MA (1)	-0.505026	0.11531	-4.38	0.0000***

Predicted Annual Inflation in Morocco

Table 15

Year	Prediction	Std. Error	95% Confidence Interval	
2018	1.1	2.79	-4.3 -	6.6
2019	1.1	3.11	-5.0 -	7.2
2020	1.1	3.40	-5.5 -	7.8
2021	1.1	3.67	-6.1 -	8.3
2022	1.1	3.92	-6.6 -	8.8
2023	1.1	4.15	-7.0 -	9.3
2024	1.1	4.38	-7.5 -	9.7
2025	1.1	4.59	-7.9 -	10.1
2026	1.1	4.79	-8.3 -	10.5
2027	1.1	4.99	-8.6 -	10.9

Table 15, with a forecast range from 2018 – 2027; clearly show that inflation in Morocco is projected to be hovering around 1.1% in the next 10 years. This implies that there will be price stability in Morocco over the next decade and the BAM should thrive to continue maintaining such stability for the benefit of all economic agents in the Moroccan economy.

CONCLUSION

The ARIMA model was employed to investigate annual inflation rates in Morocco from 1960 to 2017. The study planned to forecast inflation In Morocco for the upcoming period from 2018 to 2027 and the best-fit model was chosen based on the minimum AIC value. The ARIMA (0, 1, 1) model is stable and most suitable model to forecast inflation in Morocco for the next ten years. Based on the results, policy makers in Morocco should continue to engage proper economic policies in order to maintain macroeconomic stability in the economy.

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